



Climate change, agricultural inputs, cropping diversity, and environment affect soil carbon and respiration: A case study in Saskatchewan, Canada



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ABSTRACT

Climate change, agricultural inputs, cropping diversity, and environment have seldom been combined in analyses of soil organic carbon (SOC), and soil C respired through microbial respiration (MR). This modeling study assessed SOC and MR simulated with the Environmental Policy Integrated Climate (EPIC) model for historical weather (1971–2000) and future climate scenarios (2041–2070) for the Alternative Cropping Systems (ACS) study research site in Saskatchewan, Canada. Nineteen years of field and crop management information from the 1994–2013 ACS study were used to validate and provide parameters to the EPIC model for analyses of climate change scenarios. The ACS study consisted of three levels of agricultural inputs [organic (ORG), reduced (RED), and high (HI)] and three levels of cropping diversity [low (LOW), diversified annual grains (DAG), and diversified annuals and perennials (DAP)]. Changes in future SOC and MR under climate change were explored with ANOVA and recursive partitioning in multivariate analyses of inputs, diversity, growing season precipitation (GSP), growing degree days (GDD), annual average maximum, minimum temperatures, cumulative annual precipitation, and terrain attributes (TA). Under climate change, SOC decreased by 1.3% (from 132.3 to 130.6 Mg ha⁻¹) of original stocks in the 0–90 cm. Microbial respiration was affected by climate change and increased by 17% (from 1.92 to 2.25 Mg C ha⁻¹ y⁻¹) due to an increase in annual maximum and minimum temperatures. The increase in annual maximum and minimum temperature was correlated with 32 and 42% of variation in SOC respectively. Monthly growing season GDD was correlated with 14% of variation of SOC in an analysis independent of annual data. Annual precipitation did not affect SOC, though May GSP accounted for 16% of total variation in SOC, while June temperature accounted for 9% of variation in MR. The combination of input and diversity was correlated with 3 and 7% of variation in SOC and MR, respectively. The combination of RED inputs and DAG diversity are the best option to manage SOC and reduce the amount of soil C respired under climate change relative to organic and conventional systems.

1. Introduction

Agriculture in Canada will be influenced by climate change as temperature and precipitation regimes affect crop production. As climate change progresses, average annual and seasonal temperatures in the Prairies will rise and precipitation regimes will change

(Kulshreshtha and Wheaton, 2013). The consequences are particularly significant for the Prairies which account for 88% of soil organic carbon (SOC) in Canada's agricultural land (Minasny et al., 2017) and the majority of grain and oilseed production (Martz et al., 2007). However the effects of future temperatures and precipitation patterns on SOC in the context of microbial respiration (MR) as affected by crop and

Abbreviations: GCM, Global Climate Model; RCM, Regional Climate Model; EPIC, Environmental Policy Integrated Climate Model; PA, partition analysis; ACS, Alternative Cropping Systems Study; GSP, growing season precipitation; GDD, growing degree days; GS, growing season; ORG, organic input; RED, reduced input; HI, high input; LOW, low diversity; DAG, diversified annual grains; DAP, diversified annuals and perennials; SOC, soil organic carbon; MR, microbial respiration; TA, terrain attributes

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biomass production have not been analyzed.

Management practices such as tillage, crop rotations, and fertilizer applications may affect SOC stocks and soil properties, and the results vary among published studies. Dimassi et al. (2014) reported increases in SOC under reduced tillage at the surface (0–10 cm), but decreases at lower depths (10–28 cm) at a rate of 0.42–44% yr⁻¹. In a meta-analysis of SOC, Baker et al. (2007) concluded that analyses for depths > 30 cm are less common; conservation tillage has not resulted in consistent increases in SOC, and that SOC is redistributed with depth. Long-term studies of CO₂ fluxes show no consistent increase in C due to reduced tillage (Baker et al., 2007; Amiro et al., 2017).

Simulation models have been used to complement experimental data, and analyse the long-term effects of management on soil properties in the context of crop yield. The Environmental Policy Integrated Climate (EPIC) model is a comprehensive biophysical process model that simulates crop and biomass production, soil processes, and interactions in the system based on detailed farm management practices and climate data (Williams, 1995; Gassman et al., 2005; Izaurrealde et al., 2012). Crowther et al. (2016) concluded that model performance cannot be evaluated, or uncertainty in model projections assessed, without empirical observations that capture longer-term C dynamics. Consequently, the influence of climate change on the C cycle remains one of the largest sources of uncertainty in Earth system models. Direct field measurements of warming-induced changes in soil C stocks are not available to assess the effect of future climate projections on soil properties. Furthermore, Crowther et al. (2016) emphasized that the lack of information about the responses of soil C stocks at depth below 10 cm significantly limited analyses of warming-induced changes in regional studies.

The Alternative Cropping Systems (ACS) study provides an opportunity to assess variability in SOC due to trends in precipitation and temperature recorded over 19 years, and in response to simulated climate change as affected by tillage intensity and crop diversity. The ACS field experiment was conducted from 1994 to 2013 at Scott, Saskatchewan. To date, only a few long-term field experiments have been conducted to investigate the effects of inputs and crop diversity with respect to crop production systems and soil quality in the Canadian Prairies (Grant et al., 2016), including the ACS study. Many long-term field experiments were conducted in the USA, for example the Long-Term Ecological Research Plots in Hickory Corners, MI (1989); Blevins Long-Term Tillage Trial in Lexington, KY (1970); No Tillage Plots in Wooster, OH (1962); Crop Residue Management Experiment in Pendleton, OR (1931) and others. Long-term experiments were also conducted at the INTA Experiment Station in Cordoba, Argentina (1975), Rutherglen Center in Victoria, Australia (1912), and other countries. The uniqueness of the ACS study is that it combined rotations and agricultural input systems *typical of the Canadian Prairies*. In the ACS study, three levels of rotation and diversity were combined with organic, low, and high categories of agricultural inputs (tillage, fertilizer, pesticides) resulting in a 3 by 3 matrix. The rotations used by producers on the Canadian Prairies include summer fallow and cereal monocultures; a diversity of cereal and broadleaf crops with minimal use of summer fallow; and a combination of annual and perennial crops. The purpose of the study was to assess the impact of agricultural inputs and cropping diversity on crop production and soil quality/health, including SOC.

In previous research, Lychuk et al. (2017a) used historical and future weather scenarios, based on Regional Climate Models, to simulate wheat, canola, and barley yield with the EPIC model, in the context of agricultural inputs and cropping diversity from the ACS study. They concluded that reduced tillage and diverse annual rotations were most suited to maintain crop production under predicted climate change for

the ACS study. Thomson et al. (2005) reported that regional agriculture will be affected by climate change with consequences for regional, and eventually for national, and global food production. Regional Climate Models (RCMs) simulate temperature and precipitation at finer scales (~50 km) than most global climate models (GCMs) [e.g. 100 to 400 km (Alley, 2007)] that have previously been used to evaluate potential changes caused by climate change on agricultural systems (Reilly et al., 2003; Reilly and Schimmelpfennig, 1999; Parry et al., 1999). Thus RCMs are more relevant to simulations on regional and sub-regional levels (Lychuk et al., 2017b). Combinations of global and regional models, referred to as multi-RCM-GCM ensembles in climate change, are used to assess uncertainties of different projections of RCM models (Khalique et al., 2014). The North American Regional Climate Change Assessment Program (NARCCAP) provides climatic data for these multi-RCM and GCM ensembles (Mearns et al., 2012; Mearns et al., 2009).

This paper complements previous research by Lychuk et al. (2017a) on the effects of climate change impacts on crop yield in the context of inputs and diversity in the ACS study. The *first* objective of this study was to validate the simulation of SOC with the EPIC model. The *second* objective was to assess changes in the SOC stock (0–90 cm) and mass of soil C lost as MR due to agricultural inputs and diversified rotations simulated with EPIC model under future climate RCM-GCM projections for similar initial conditions. The *third* objective of this study was to identify management which reduces the environmental impact of climate change on SOC and MR. The conceptual flow diagram (Fig. 1) shows the workflow of this modeling study with respect to (1) variables for the EPIC model from the ACS study, (2) model validation with experimental SOC, (3) historical and future climate scenarios for the EPIC model used to simulate SOC and MR and (4) comparisons of SOC and MR simulated by the EPIC model between climate scenarios.

2. Materials and methods

2.1. The 1994–2013 alternative cropping system (ACS) rotation study

The ACS experiment was established in 1994 and completed in 2013 at the Agriculture and Agri-Food Canada Research Farm at Scott, Saskatchewan (52°22'N; 108°50'W; elevation 713 m). The soil was a Dark Brown Chernozem (coarse-loamy textured mesic Typic Haploboroll, US Soil Classification) (Table 1) developed from modified glacial till (Clayton and Ellis, 1952) with slopes from 1 to 3%. Nine cropping systems, each 6 years in length, were initiated in 1995, following a uniformity trial in 1994. The nine cropping systems were combinations of three input management strategies applied to three levels of cropping diversity (Table 2). In this study, cropping system refers to a particular combination of an input × diversity level. For example, the ORG × LOW system refers to low diversity cropping rotations (based on wheat and fallow) within organic input (i.e. where tillage is a primary mechanism to manage weeds with no fertilizer or chemical pest management). The three input levels were: (1) organic (ORG, based on weed control with tillage, and non-chemical pest management and nutrients to reflect practices used by organic growers); (2) reduced (RED, no-till with integrated management of nutrients based on soil test recommendations and pests management); and (3) high (HI, used conventional rates of pesticides and fertilizers, with tillage). The three diversity levels were: (1) low diversity system (LOW, based on the combination of wheat, canola, and fallow); (2) diversified annual grains system (DAG, diverse cereal, oilseed and pulse crops); and (3) diversified annuals and perennials system (DAP, mix of grain and forage crops). The experiment was designed as a split-plot with four replications. Input level was main plot, crop diversity and crop phases were sub, and sub-sub plots, respectively. The size of the

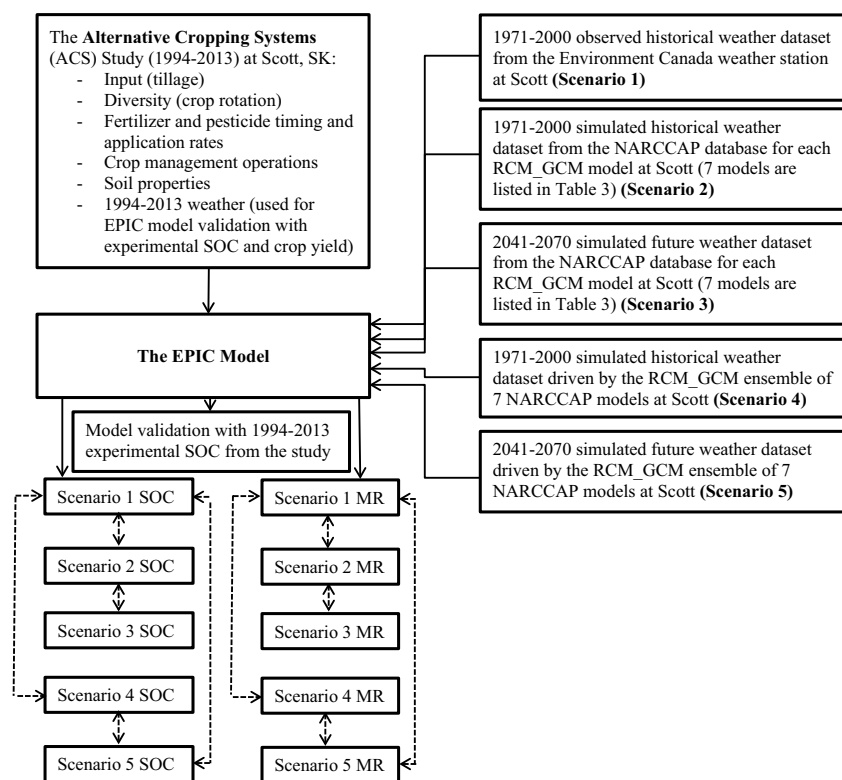


Fig. 1. Conceptual diagram describing (1) variables for the EPIC model from the ACS study; (2) the EPIC model validation with experimental SOC; (3) observed historical baseline weather, and RCM_GCM driven historical and future climate scenarios for the EPIC model used to simulate SOC and MR; (4) outputs of simulated SOC and MR by the EPIC model and their comparisons between climate scenarios (indicated by the dashed lines). Abbreviations: ACS - the Alternative Cropping Systems Study; EPIC - the Environmental Policy Integrated Climate model; SOC - soil organic carbon; MR - microbial respiration.

Table 1
Characteristics of the soil profile by depth increment.

Property	Depth increment					
	1	2	3	4	5	6
Lower boundary, m	0.07	0.15	0.30	0.60	0.90	1.20
Physical ^a						
Soil texture, g kg ⁻¹						
Sand	696	696	654	632	579	547
Clay	99	99	107	119	132	147
Bulk density, Mg m ⁻³	1.16	1.33	1.36	1.52	1.74	1.88
May soil temperature (5 cm/10 cm), °C ^b	10.93/9.92	–	–	–	–	–
Spring soil moisture, mm ^c	–	37.77	34.07	45.29	45.93	–
Harvest soil moisture, mm ^c	–	24.54	24.71	35.52	37.91	–
Organic carbon, % ^a	3.2	2.6	1.2	0.8	0.4	0.3
Chemical						
pH ^a	5.1	5.6	6.0	6.5	6.5	6.5
NO ₃ -N, kg ha ^{-1a}	–	38.42	11.78	11.93	18.84	26.14
PO ₄ -P, kg ha ^{-1a}	–	34.50	9.30	6.27	4.01	3.19
C/N ratio ^a	10.39	9.89	–	–	–	–

^a Data from A.P. Moulin and F. Selles, Agriculture and Agri-Food Canada, Brandon Research Center and Semiarid Prairie Agricultural Research Center (unpublished data).

^b Data from R. Weiss, Agriculture and Agri-Food Canada, Saskatoon, SK and Scott Experimental Farm (unpublished data).

^c Data from S.A. Brandt and R. Weiss, Agriculture and Agri-Food Canada, Saskatoon, SK and Scott Experimental Farm (unpublished data).

experimental site was 16 ha, and the dimensions of each subplot were 40 m × 12.8 m.

2.1.1. Tillage

The ORG and HI input systems were tilled in the fall to manage crop residues and control weeds, while a fall application of phenoxy herbicides (2,4-D or MCPA) was typically used for fall weed control in the

Table 2
Description of the nine cropping systems in the Alternative Cropping System (ACS) study^a.

Diversity level ^b	Input level ^c	Cropping rotation
LOW	ORG	GM ^d -Wheat-Wheat-GM-Mustard ^e -Wheat
	RED	GM ^d -Wheat-Wheat-Chem. Fallow ^f -Canola-Wheat
	HI	Fallow ^g -Wheat-Wheat-Fallow ^g -Canola-Wheat
DAG	ORG	GM-Wheat-Pea-Barley ^h -GM ⁱ -Mustard ^e
	RED	Canola-Fall rye ⁱ -Pea-Barley-Flax-Wheat
	HI	Canola-Fall rye ⁱ -Pea-Barley-Flax-Wheat
DAP	ORG	Mustard ^e -Wheat-Barley-Alfalfa ^k -Alfalfa-Alfalfa
	RED	Canola-Wheat-Barley-Alfalfa ^k -Alfalfa-Alfalfa
	HI	Canola-Wheat-Barley-Alfalfa ^k -Alfalfa-Alfalfa

^a Source: Brandt et al., 2010.

^b LOW - low; DAG - diversified annual grains; DAP - diversified annuals and perennials.

^c ORG - organic, non-chemical pest control and nutrient management; RED - reduced, integrated long-term management of pests and nutrients utilizing chemicals and no-till practices; HI - high, pesticides and fertilizers “as required” based on conventional recommendations associated with pest thresholds and soil tests.

^d GM - green manure (Indian Head Lentil) partial fallow.

^e After the first cycle canola was replaced with mustard.

^f Chem. fallow - summer fallow with weeds controlled by herbicides.

^g Fallow - summer fallow with weeds controlled by tillage.

^h Barley was under seeded to sweet clover in first two cycles.

ⁱ Sweet clover in first two cycles.

^j In the third cycle, fall rye was replaced with soft white spring wheat.

^k In the first cycle, alfalfa and brome were under seeded to oat in the forage establishment year.

RED system. Tillage was rarely used in the RED system except to terminate alfalfa stands in the DAP system. Plots were cultivated prior to planting, for weed control and seed-bed preparation. In the ORG and HI input systems, pre-plant tillage typically consisted of one to two operations with a sweep-type cultivator followed by harrowing or harrow-packing. In RED systems, plots were harrowed to spread crop residue,

or to prepare the seedbed after fall tillage when alfalfa was terminated in the RED-DAP system. Herbicides were used for pre-planting weed control in the RED system. In the ORG systems, weeds were controlled with a harrow in-crop in the cereal and pea cropping phases. Plots were tilled throughout the growing season in the fallow phases of the ORG-LOW, ORG-DAG, and HI-LOW systems. The number of tillage operations required after green manure in the ORG systems was about half the number for conventional summer fallow in the HI system.

2.1.2. Seeding

Lentil green manure was typically seeded first, followed by pea, oilseeds, and then cereals. Crops common to more than one diversity system were seeded on the same day in each of the diversity treatments of an input system. Lentil green manure was seeded in late April to early May to allow the crop to develop in advance of weeds, as lentil recovers well if damaged by spring frosts. Crops in the ORG systems were generally seeded later than HI and RED to allow for cultivation of one or more flushes of weeds prior to planting. On average, HI systems were seeded 2 days later than the RED and 5–16 days earlier than ORG.

At the beginning of the study, all crops were seeded with a 20-cm row space hoe press drill. In the second and third 6-yr cycles, the HI and RED systems were seeded with a 25-cm row space drill and a 15-cm row space double disc press drill was used for the ORG systems. The wider row spacing in the HI and RED systems was selected to minimize plugging with crop residues. Row spacing was reduced to 15 cm in the ORG systems to increase crop competition with weeds.

Crop cultivars were selected based on suitability for soils and climate normals typical of the Dark Brown Soil Zone in this area of Saskatchewan (Saskatchewan Seed Growers Association, 1994–2013; Campbell et al., 2002). The same cultivars were used for all input and diversity systems in each 6-year rotation cycle, whenever possible. Crops were seeded according to recommended rates in the HI input systems and generally at 33% higher rates in the ORG and RED systems to increase competition with weeds.

2.1.3. Fertilizer and nutrient management

Fertilizer, cultural and crop protection practices for the study were described by Brandt et al. (2010). In summary, prior to the establishment of treatments in 1994, fertilizer was applied in a mid-row band at seeding at rates of 39 kg ha⁻¹ of 46-0-0 (N-P-K) and 50 kg ha⁻¹ of 12-51-0 over the entire site to minimize residual fertility variations prior to establishment of experimental treatments in 1995. In the RED and HI input systems, N, P, K, and S fertilizers were applied at or before seeding at rates based on soil test recommendations (Saskatchewan Soil Testing Laboratory, 1990). Fertilizer rates for the HI systems were based on the mean for all replicates of a treatment, while those in the RED systems were determined from soil test data for plot averages within replicates. Differences in replicate-based rates in the RED system were generally small (data not shown). Fertilizer rates tended to be lowest for the LOW diversity systems, and highest for the DAG systems, where grain crops were grown every year. Fertilizer phosphate was applied with the seed to the RED and HI input treatments at constant rates across replicates based on soil test recommendations (Saskatchewan Soil Testing Laboratory, 1990).

2.2. Data collection and soil sampling

In 1994, prior to establishment of the experimental treatments, the site area was seeded to barley and uniformly fertilized to minimize spatial variability of residual fertility (Lychuk et al., 2017c). Barley yield and baseline soil properties were measured at 160 locations in a systematic unaligned grid across the experimental area (Selles et al.,

1999). Two cores from the depth of 15 cm were collected at each sample location. Cores were divided into 0 to 7.5 cm and 7.5 to 15 cm depth increments and composited by depth increment per sampling location. These samples were then sieved (< 2 mm), air-dried, and stored at 1 to 3 °C prior to analysis (Selles et al., 1999). Deep soil cores were also taken from 0 to 120 cm and 0–240 cm depths. Organic and total C and N, pH, bulk density, and particle size distribution were determined from these samples and were used for the EPIC model initialization. Organic C was determined by an automated combustion technique (Carlo Erba™, Milan, Italy). Soil pH was measured with a pH meter using 20 g soil in 40 mL dilute CaCl₂ solution. Particle size distribution was determined by the hydrometer method (Sheldrick and Wang, 1993). In addition, organic C was determined from soil samples collected at the end of each 6-yr cycle (2000, 2006, and 2012). Further details with regards to sampling and procedures used for organic C determination at the end of cycles may be found in Malhi et al. (2009).

2.3. EPIC model, climatic input data and simulations

Nineteen years of crop yield, soils and meteorological data from the Alternative Cropping System (ACS) study were used to validate and calibrate the EPIC model with experimental crop yield (Lychuk et al., 2017d) and SOC (below). The EPIC model was updated with tillage, soil properties, crop management, fertilizer and pesticide application rates, information on input and diversity treatments from the ACS study described in Section 2.1, and recorded historical weather (Environment Canada, 2014) at Scott from 1994 to 2013. The EPIC model (v 1102) simulations were run with soil properties and management for each plot in the first replicate as determined in 1994, combined with daily data for each year of the climate scenarios. Data for replicates 2, 3 and 4 in the experiment were not included in the simulations due to logistical constraints. The model calculated soil C and N based on substrate-specific rate constants, temperature, and water content in a daily time step. Carbon and N fluxes were calculated based on the N supply for each soil process (Izaurralde et al., 2006). Soil organic carbon is the mass (Mg ha⁻¹) in a stock which represents annual mean for the soil profile (0–90 cm), simulated in the model based on 15 cm increments on dynamic soil profile basis in the EPIC model. The mass of soil C respired by soil microbes is the flux (kg ha⁻¹ d⁻¹) derived from a daily average from allocations of carbon fractions to CO₂ and microbial biomass (Izaurralde et al., 2006; Izaurralde et al., 2017). Daily evapotranspiration was calculated based on the Penman-Monteith equation. The EPIC model was described in detail by Gassman et al. (2005); further information on EPIC algorithms and a detailed description of the model are in Izaurralde et al. (2006). Soil organic carbon and microbial respiration for the canola, wheat and barley phases of combinations of input and diversity in each year of the rotations over 30 year simulations ($n = 799$), are discussed.

Weather data from historical databases, RCMs and related GCMs, were used to simulate soil properties with the EPIC model (Table 3). Temporal trends in soil properties were determined for each simulation period, while means and associated error for SOC (0–90 cm) and mass of soil C loss as MR were calculated across all years ($n = 30$) for each simulation period, 1971–2000 and 2041–2070. Five climate datasets, listed below, were input into the EPIC model, in separate scenarios (Fig. 1), to compare differences in simulated SOC and MR by the EPIC model between the datasets in the context of input and diversity levels at Scott:

1. Observed historical weather dataset (1971–2000) obtained from the Environment Canada (Environment Canada, 2014) weather station;
2. Simulated historical weather dataset (1971–2000) from the

Table 3

Meta-data for observed historical baseline weather (HIST, 1971–2000) and historical/future weather from the North American Regional Climate Change Assessment Program's (NARCCAP)^a.

Regional Climate Model	Driving Global Climate Model	Acronym of the GCM_RCM simulation	Period of simulation (historical/future)	Model's temporal/spatial resolution/distance from the research field at Scott
1971–2000, HIST.	–	HIST.	1971–2000	Daily/~1 km
Canadian Regional Climate Model: CRCM	Canadian Global Climate Model, version 3: CGCM3	CRCM_CGCM3	1971–2000/2041–2071	3 h average/~50 km/~10 km
	Community Climate System Model, version 3: CCSM	CRCM_CCSM	1971–1999/2041–2070	3 h average/~50 km/~10 km
Hadley Regional Climate Model: HRM3	Geophysical Fluid Dynamics Laboratory Model: GFDL	HRM3_GFDL	1971–2000/2041–2070	3 h average/~50 km/~20 km
Regional Climate Model 3: RCM3	GFDL	RCM3_GFDL	1971–2000/2041–2070	3 h average/~50 km/~30 km
	CGCM3	RCM3_CGCM3	1971–2000/2041–2070	3 h average/~50 km/~30 km
Weather Research and Forecasting Model: WRFG	CGCM3	WRFG_CGCM3	1971–2000/2041–2070	3 h average/~50 km/~25 km
	CCSM	WRFG_CCSM	1971–2000/2041–2070	3 h average/~50 km/~25 km

^a Adapted from Khaliq et al. (2014); Monette et al. (2012); Mailhot et al. (2012).

NARCCAP database for each RCM_GCM model (7 models are listed in Table 3);

3. Simulated future weather dataset (2041–2070) from the NARCCAP database for each RCM_GCM model (7 models are listed in Table 3);
4. Simulated historical weather dataset (1971–2000) driven by the RCM_GCM ensemble of 7 NARCCAP models;
5. Simulated future weather dataset (2041–2070) driven by the RCM_GCM ensemble of 7 NARCCAP models.

In this paper, RCM simulations are referred to as 'RCM_GCM'. The RCM represents the acronym of the Regional Climate Model and GCM for the global climate model's driving boundary condition (Monette et al., 2012; Khaliq et al., 2014). For instance, the Canadian Regional Climate Model (CRCM) simulations forced by the Community Climate System Model (CCSM) global model are referred to as CRCM_CCSM.

Tillage, soil properties, crop management, fertilizer and pesticide application rates, input and diversity treatments from the ACS study at Scott were input to the EPIC model, with observed historical baseline weather (1971–2000) in scenario 1, and simulated historic (1971–2000) and future (2041–2070) weather from RCM_GCM models (Table 3 and Fig. 1) in scenarios 2 to 5. Wind speed, precipitation, relative humidity, solar radiation, maximum and minimum temperatures (calculated for 3 h intervals) from the NARCCAP climate database were converted to daily means for simulated historic (1971–2000) and future (2041–2070) weather used in RCM_GCM models, and were input to the EPIC model in scenarios 2 to 5. In scenario 1 with observed historical baseline weather (1971–2000), daily weather variables, with the exception of solar radiation, were from the Environment Canada (Environment Canada, 2014) weather station at Scott. Solar radiation data were estimated from sunshine hours simulated by the EPIC model weather generator (WXGEN) (Richardson, 1981; Richardson and Wright, 1984).

Simulations with historic and future weather were conducted under CO₂ concentration of 344 (scenarios 2 and 4) and 560 (scenarios 3 and 5) ppmv, respectively (Mearns et al., 2009; Mearns et al., 2012; Mearns et al., 2013). The starting point for future simulations was year 2041 in the context of significant climate change effects predicted for the late 2030's to the early 2040's (IPCC, 2007; IPCC, 2014). The spatial resolution of the RCM_GCM models was 50 km. Descriptions of each RCM are available at the NARCCAP web sites (Mearns et al., 2012; Mearns et al., 2013). Regional distributions, and deviations from the historical baseline of air temperatures and precipitation, were predicted with four combinations of RCM and GCM models (Table A1). The monthly (April–September) average GSP for the majority of the climate change models and the ensemble average, was significantly ($P < 0.05$) higher compared to the historical observed baseline mean, except for August and September (Table A2). Similarly, the monthly average GDD was significantly higher than the observed historical baseline mean for the

majority of the climate scenarios and the ensemble average, except for May, August and September.

2.4. Terrain attributes at the Scott research site

Fifty-three terrain derivatives and attributes were calculated with the System for Automated Geoscientific Analysis (SAGA) (Böhner and Antonić, 2009; Böhner et al., 2006) from elevation data collected in 1994. Previous analyses of experimental data showed that surface curvature and other terrain attributes were significantly correlated with crop yield in dry years (Lychuk et al., 2017c). Terrain attributes were not included in the model simulations because the EPIC model was not designed to account for the effects of micro-topography apart from unified slope, a steepness factor, and the field aspect. For this reason, in this study terrain attributes for each plot in the first replicate determined at the beginning of the study were included in the statistical analysis as covariates to account for their influence on soil properties, such as soil moisture and nutrient distribution, which may affect SOC and MR. These terrain attributes included relative slope position, surface convexity, direct and diffuse insolation, catchment slope, profile curvature, and maximum height. Plot averages of terrain attributes and crop yield (barley from a uniformity trial conducted in 1994 prior to treatments initiated in 1995) were interpolated for each plot with ordinary kriging (Davis, 2002). Relative slope position refers to the position of the slope within the landform (upper, middle, and lower slope). Slope measures the rate of change of elevation in the direction of steepest descent. Slope is the means by which gravity induces flow of water and other materials (Wilson and Gallant, 2000a; Wilson and Gallant, 2000b). Surface convexity is positive in convex-upward areas, negative in concave areas, and zero on planar slopes (Iwahashi and Pike, 2007). Direct insolation represents unimpeded solar insolation intercepted by land area perpendicularly from the sun, as opposed to diffuse insolation. Profile curvature is the rate of change of slope down a flow line.

2.5. Statistical analysis

All statistical analyses were done with JMP®, Version 12.0.0 (SAS Institute Inc, 2015). Soil organic carbon (0–90 cm) and MR simulated by the EPIC model were compared between the observed historic (scenario 1) baseline (1971–2000), RCM_GCM model driven simulated historic (scenarios 2 and 4) (1971–2000), and RCM_GCM model driven future (scenarios 3 and 5) simulated weather (2041–2070) (refer to Fig. 1 and Section 2.3 for specific details on comparisons made). Statistical analyses and ANOVA included SOC and MR as dependent variables, year and replicate as random effects, and agricultural input (main fixed effect) and cropping diversity (subplot) as independent variables. Variables which accounted for a high proportion of the

variability in PA, were included as covariates in the ANOVA, and were further assessed with the variance inflation factor (JMP 12.0, SAS Institute Inc, 2015) to confirm that they were not correlated. Data were analyzed with a MIXED model (ANOVA), and an analysis of covariance (ANCOVA) in JMP. Statistical analyses are reported for fixed effects, though random effects were included in the ANOVA. Treatment effects were declared significant at $P < 0.05$, and means were compared with the Tukey Honest Significant Difference (HSD) test. Tukey HSD test performs all pairwise comparisons to detect means which are significantly different from each other, while protecting for Type I error. Terrain attributes, total monthly GSP and GDD (from April to August) were included or excluded based on exploratory analysis in PA, prior to the ANOVA/ANCOVA. Annual average maximum, minimum temperatures and cumulative annual precipitation were analyzed separately as covariates on SOC and MR in the ANOVA/ANCOVA due to significant collinearity. The relative importance and proportion of variance related to each variable were not the same in PA and ANOVA, as some variables were removed from the data set following preliminary analyses with PA. Terrain attributes, barley yield from the uniformity trial, GSP and GDD were included in statistical analysis as covariates to account for spatial and temporal autocorrelation (Loughin et al., 2007) of SOC and MR associated with environmental factors in the future climate scenarios 3 and 5. Linear regression and coefficients of determination (R^2), root mean square error of prediction (RMSE) (Willmott and Matsuura, 2005), and the d index (Willmott, 1984) were used to validate the EPIC model in order to assess temporal trends and the relationship between simulated and experimental SOC. The RMSE and d index were calculated as follows:

$$\text{RMSE} = \left[n^{-1} \sum_{i=1}^n (y_i - x_i)^2 \right]^{0.5} \quad (1)$$

$$d = 1 - \left[\frac{\sum_{i=1}^n (y_i - x_i)^2 / \sum_{i=1}^n (y_i - x_{\text{avg}})^2 + (x_i - x_{\text{avg}})^2}{\sum_{i=1}^n (y_i - x_i)^2 / \sum_{i=1}^n (y_i - x_{\text{avg}})^2 + (x_i - x_{\text{avg}})^2} \right] \quad (2)$$

where y = simulated, x = experimental, and x_{avg} = average of experimental SOC. The d index is a descriptive measure to evaluate model performance. A d statistic of < 0.7 , 0.7 to 0.8 , 0.8 to 0.9 , and > 0.9 indicates poor, moderate, good and excellent agreement of model performance respectively in relation to the experimental data (Willmott, 1984).

Recursive partition analysis (PA) was used in multivariate analyses of simulated SOC (0–90 cm), and MR. These variables were assessed in the analysis to identify which agricultural input systems, rotations, GSP, GDD accounted for the most variability. Baseline covariates which characterize spatial variability at site, such as terrain attributes and barley yield from a uniformity trial, were also included in the analysis. Details of this statistical analysis are described in Lychuk et al. (2017c) and Lychuk et al. (2017a). Recursive partition analysis has several advantages relative to other methods of multivariate analyses; it is a supervised method which accounts for variation due to continuous and categorical (nominal or ordinal) variables in exploratory data analysis. Partition analysis is more robust to non-normalities in data distribution compared to other types of analyses, such as principal component analysis, which works best for continuous, normally distributed data (Rummel, 1988; Mardia et al., 1979; Jolliffe, 2003). In this study, data were analyzed with decision trees, a variant of PA. Percent variation of independent variables in partition analysis may differ from a mixed-design analysis of variance (ANOVA) where the variance is calculated with restricted maximum likelihood.

Table 4

Experimental and simulated soil organic C (0–15 cm) calculated from average data of each 6 year cycle (1995–2000, 2001–2006, 2007–2012) of the Alternative Cropping Systems study for factorial combinations of Organic (ORG), Reduced (RED), High (HI) input and Low (LOW), Diversified Annual Grains (DAG), and Diversified Annuals and Perennials (DAP).

Input by Diversity treatment interactions	Soil organic C					
	Experimental	Simulated by EPIC	RMSE ^z	Error, % ^y	R^2 ^x	d ^w
	Mg ha ⁻¹					
ORG-LOW ^v	42.8	43.9	0.15	2	0.99	0.69
ORG-DAG ^v	43.7	44.3	0.81	1	0.98	0.67
ORG-DAP ^v	43.8	44.1	1.66	< 1	0.91	0.60
RED-LOW	41.1	45.4	2.33	10	0.92	0.61
RED-DAG	44.2	45.7	0.83	3	0.97	0.82
RED-DAP	44.3	46.2	4.05	4	0.27	0.58
HI-LOW	42.6	42.7	0.90	< 1	0.96	0.97
HI-DAG	42.0	44.0	1.51	5	0.66	0.62
HI-DAP	42.1	44.1	0.07	5	0.99	0.77

^{a,b} Letters indicate significant differences between experimental and simulated yield per crop at the 5% level according to the paired t -test or Wilcoxon signed rank test.

^z Root mean square error.

^y % error calculated from (Simulated-Experimental)/Experimental * 100.

^x Coefficient of determination

^w d index.

^v Under ORG input, canola was grown only in the first 6-year cycle of the study.

3. Results

3.1. Validation of the EPIC model with 1994–2013 experimental SOC

The EPIC model was validated with experimental SOC data for 1994–2013 from the ACS study, with statistical analyses similar to those for crop yield (Lychuk et al., 2017d). In these analyses, the EPIC

Table 5

Soil organic C and mass of soil C lost through microbial respiration simulated by the EPIC model over observed historical baseline (Scott 1971–2000) and future (2041–2070) simulation periods. Future climate scenarios were predicted by the RCM GCM models and model ensemble average. Models in ensemble are listed in Table 3.

Model	Soil organic carbon Mg ha ⁻¹	Micr. resp. Mg C ha ⁻¹ y ⁻¹
Soil depth cm		0–90
Scott 1971–2000 (observed historical baseline)	132.2a	2.20ab
CRCM_CGCM3	133.2b	2.69b
CRCM_CCSM	130.2e	2.11b
HRM3_GFDL	128.4f	2.17ab
RCM3_GFDL	133.8c	2.59d
RCM3_CGCM3	130.4de	2.76b
WRFG_CGCM3	128.3f	1.85e
WRFG_CCSM	128.5f	1.60f
Ensemble average	130.6d	2.25a
Standard error of the difference ^a	0.25	0.02

Letters within the same column indicate Tukey Honest Significant Mean Differences at $P < 0.05$.

$n = 779$.

^a Tukey Honest Significant Mean Differences standard error of the difference.

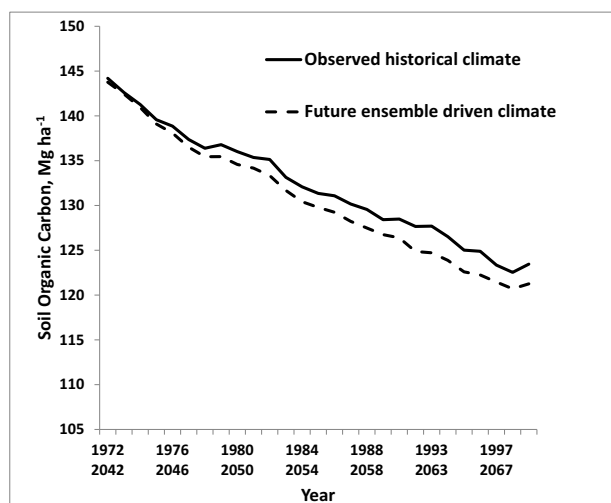


Fig. 2. Simulated annual soil organic C (Mg ha^{-1}) (0–90 cm) by the EPIC model across all input and diversity levels for 1971–2000 observed historical baseline weather (scenario 1) and 2041–2070 future weather (scenario 5). Future 2041–2070 climate was predicted by the RCM_GCM model ensemble average. Models in ensemble are listed in Table 3.

model was updated with tillage, soil properties, crop management, fertilizer and pesticide application rates, input and diversity treatments, and recorded historical weather (Environment Canada, 2014) at Scott from 1994 to 2013. The EPIC model accurately predicted changes in SOC as a function of inputs and crop diversity. Experimental and simulated SOC were not significantly different in comparisons by combinations of input \times diversity (Table 4). These data show that the EPIC model may be used to predict changes in long-term SOC for this case study.

3.2. Effects of climate change on SOC and MR across all levels of input, diversity and terrain attributes

3.2.1. Observed historical baseline (1971–2000) and RCM_GCM driven simulated future (2041–2070) scenarios

Soil organic C (Mg ha^{-1}) (0–90 cm), simulated by the EPIC model across all input and diversity treatments for 2041–2070 with the

RCM_GCM model ensemble (scenario 5), was 1.2% lower ($P < 0.05$) (Table 5 and Fig. 2) relative to SOC under the observed historical baseline weather (1971–2000) (scenario 1). Soil organic carbon decreased at a significantly higher rate ($P < 0.0001$) for the future ensemble driven climate relative to the observed historical data. Simulated MR for 2041–2070 was not significantly higher ($P > 0.05$) than in 1971–2000 (Table 5). Overall, SOC decreased, due to climate change, at higher rates relative to historical weather (ANCOVA test, $P < 0.01$) (Fig. 2), though individual regional/global models contributed to bias related to variability in monthly GSP and GDD. Model bias, calculation of average, uncertainty range, and reliability of regional climate change via the REA method and their results were reviewed in detail by Lychuk et al. (2017a).

The differences in SOC and MR between individual models (scenario 3) were related to precipitation and temperature affected by climate change. For example, MR was highest (Table 5) for the models that predicted high-future GSP and GS temperatures (RCM3_CGCM3, Fig. A1b,c). The greatest reductions in SOC, compared to historical values, were simulated by models, such as HRM3_GFDL that predicted increases in future minimum GS temperatures, (Fig. A1b) (Table 5). At the same time, SOC was highest (Table 5) for models that predicted highest increases in future GS precipitation (RCM3_GFDL, Fig. A1c).

3.2.2. RCM_GCM driven simulated historical (1971–2000) and future (2041–2070) scenarios

Ensemble analysis (scenarios 4 and 5) with 7 models, indicated that under climate change, SOC decreased by 1.3% of original stocks (from 132.3 to 130.6 Mg ha^{-1}) in the soil profile (0–90 cm), while MR increased by 17% (from 1.92 to 2.25 $\text{Mg C ha}^{-1} \text{y}^{-1}$) compared to simulated historical values (paired t -test, $P < 0.05$) (Fig. 3). Soil organic carbon decreased (1.3 vs 1.2%), and MR increased (17% vs. 2%) for 2041–2070, relative to the simulation with 1971–2000 observed historical baseline weather data (section 3.2.1).

3.3. Effects of agricultural inputs and cropping diversity in simulations of SOC and MR in the context of climate change, GSP, GDD and terrain attributes

3.3.1. Soil organic carbon

Soil organic carbon was high ($\sim 136 \text{ Mg ha}^{-1}$, 0–90 cm) at the beginning of the study in 1994. Inputs significantly affected SOC when 30 years of past and future climate scenarios were assessed with field

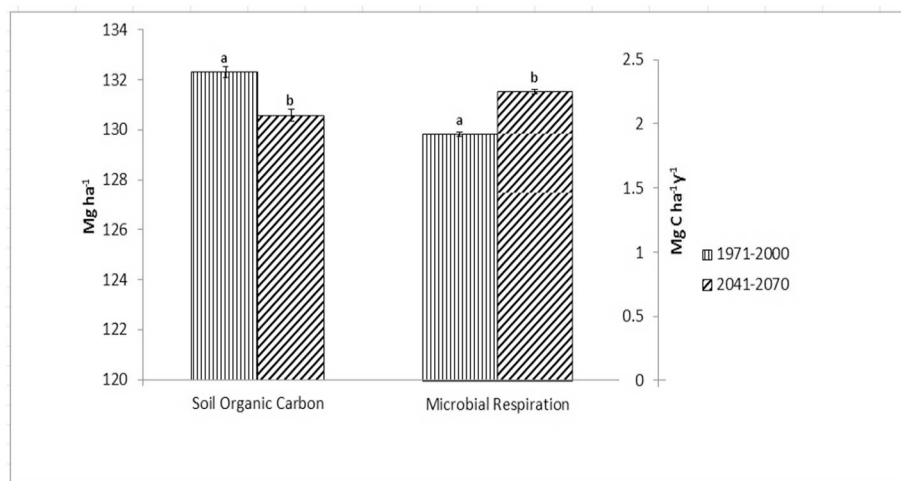


Fig. 3. Average 30-year soil organic C (Mg ha^{-1}) (0–90 cm) and mass of soil C lost through microbial respiration ($\text{Mg C ha}^{-1} \text{y}^{-1}$) calculated from annual values for 2041–2070 simulated by the EPIC model under historic (1971–2000) (scenario 4) and future (2041–2070) (scenario 5) climate scenarios. Historic and future climate scenarios were simulated with the RCM_GCM model ensemble average. Models in ensemble are listed in Table 3. Error bars represent $+1/-1$ standard error of the mean calculated from annual values for 1971–2000 and 2041–2070 simulated with EPIC model. Letters indicate significant differences for a paired t -test, $P = 0.05$. $n = 779$.

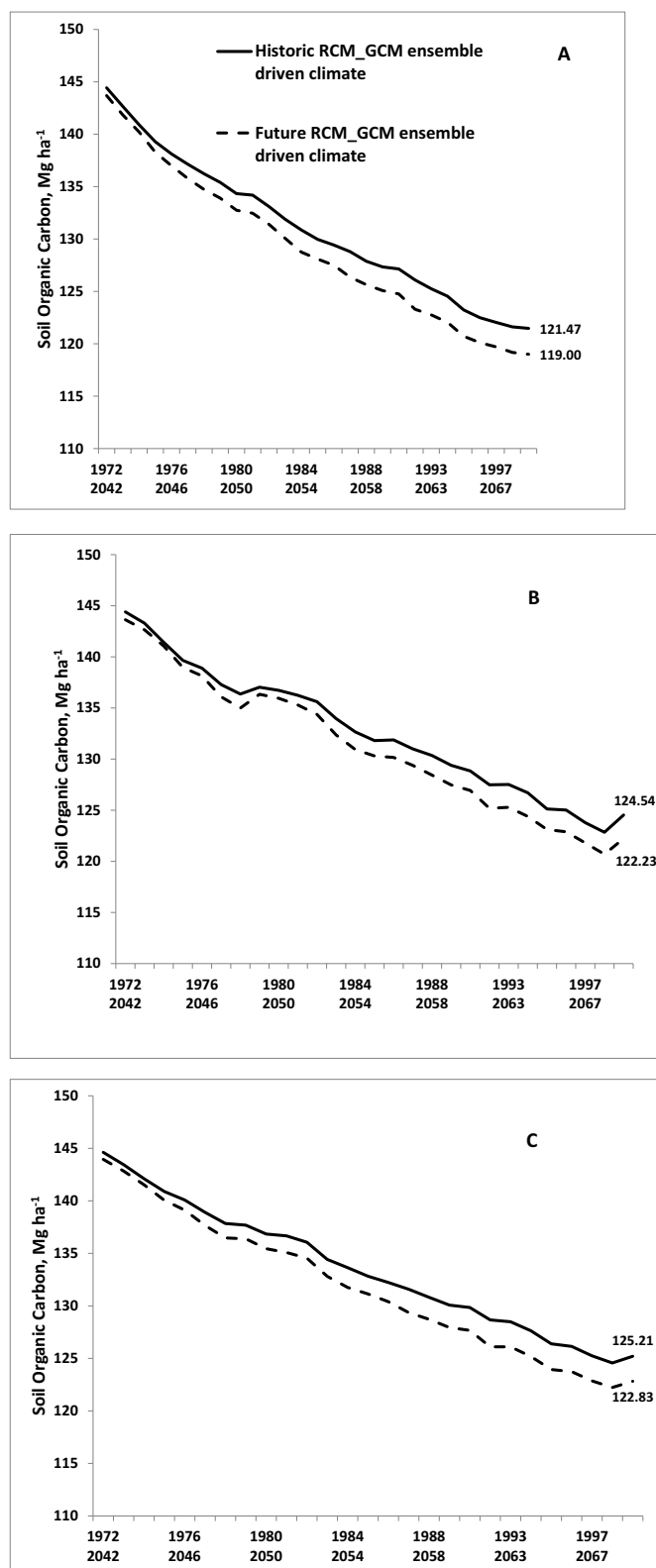


Fig. 4. Simulated annual soil organic C (Mg ha^{-1}) (0–90 cm) in (A) High, (B) Organic, and (C) Reduced inputs by the EPIC model under historic (1971–2000) and future (2041–2070) climate scenarios 4 and 5. Numbers at the end of lines show final SOC content at the completion of historic (2000, solid line) and future (2070, dotted line) simulation period). Historic and future climate was predicted by the RCM_GCM model ensemble average. Models in ensemble are listed in Table 3.

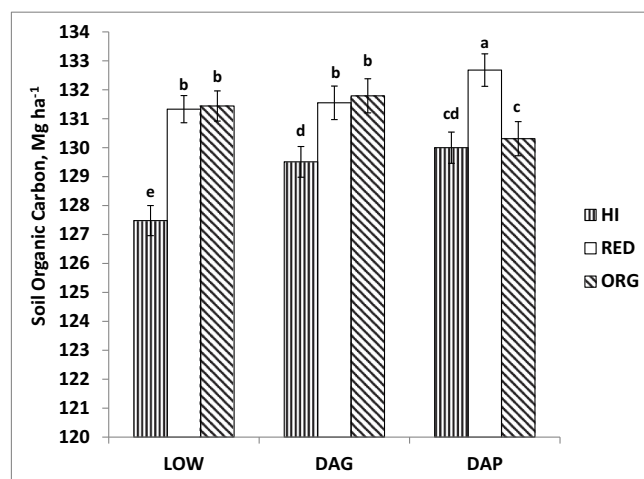


Fig. 5. Effects of input (high – HI; reduced – RED; organic – ORG) and cropping diversity (low – LOW; diversified annual grains – DAG; diversified annuals and perennials – DAP) on 30-year (2041–2070) average soil organic C (0–90 cm) calculated from annual values for 2041–2070 simulated by the EPIC model under future climate (scenario 5). Models in ensemble are listed in Table 3. Means within and between each combination followed by the same letter do not differ at $P = 0.05$, based on Tukey's HSD. Error bars represent ± 1 standard error of the mean calculated from annual values for 2041–2070 simulated with EPIC model. $n = 779$.

and crop management in the ACS study. Soil organic carbon (0–90 cm) varied significantly in simulations of HI (129 Mg ha^{-1}), ORG (131 Mg ha^{-1}), and RED (132 Mg ha^{-1}) inputs. In simulations with observed historical baseline weather (1971–2000) (scenario 1), SOC was highest for RED (133 Mg ha^{-1}) and lowest for HI (131 Mg ha^{-1}) input. Time series (Fig. 4a,b,c) for SOC under RCM_GCM ensemble driven climate change (scenario 5) showed a significant decline for all three input systems relative to RCM_GCM ensemble driven historical weather (scenario 4) (ANCOVA test, $P < 0.01$).

Soil organic carbon decreased till 2068 in simulations, from the high original initial organic C content at this site. This decrease occurred at a higher rate in high, relative to organic and reduced, input systems, and under future compared to historical climate in regression analysis ($P < 0.0001$). However, the decrease in SOC was slowest in the RED relative to other inputs (ANCOVA test, $P < 0.01$) (Fig. 4a,b,c). Simulations show that SOC will reach equilibrium in 2068, for ORG and RED tillage, at which point the system will start accumulating SOC (Fig. 4a,b,c).

Soil organic C simulated by the EPIC model under RCM_GCM ensemble model for 2041–2070 (scenario 5) was highest under RED \times DAP (Fig. 5). Simulations of SOC by EPIC under observed historical baseline weather (1971–2000) (scenario 1) indicated that SOC for ORG \times DAG was high (133.4 Mg ha^{-1}) and not significantly different than RED \times DAP (134.1 Mg ha^{-1}). However, simulated SOC with EPIC under the 2041–2070 RCM_GCM ensemble model (scenario 5) was lower in ORG \times DAG than RED \times DAP (Fig. 5). Soil organic C was lowest in the HI \times LOW system (Fig. 5). Soil organic C was also lowest for the same system in simulations under 1971–2000 observed historical baseline weather (129 Mg ha^{-1}) (scenario 1).

Tillage reduced SOC in HI combined with LOW, relative to RED and ORG, as the number of operations was twice that of other treatments. Furthermore there was little or no residue at the surface when tillage was combined with fallow phases in LOW.

Soil organic C in climate change scenarios with the RCM_GCM model ensemble (scenario 5) was primarily influenced by precipitation in summer and fall as well as by spring temperatures (Table 6), based on partition analysis. Increases in annual maximum and minimum temperatures were correlated with 32 and 42% of variation in SOC

Table 6

Percent variation from partition analysis of the effects of input (main plots) and diversity (sub-plots) on soil organic C and microbial respiration (mass of soil C respired) with monthly growing season precipitation, growing degree days, and terrain attributes under future climate (2041–2070) scenario 5. The RCM_GCM models in ensemble are described in Table 3.

Variable	Effect																	
	Inp.	Div.	Growing season precip.					Growing degree days					Terrain attributes					
			Apr	May	Jun	Jul	Sep	Apr	May	Jun	Jul	Aug	RSP ^a	SC ^b	DI ^c	BY ^d	MH ^e	CS ^f
SOC	–	–	–	11	–	19	30	33	–	< 1	–	6	–	–	–	–	–	–
Microbial respiration	< 1	–	–	22	6	15	10	6	–	23	8	3	–	–	5	3	–	–

Note: Percent variation of independent variables in partition analysis may vary from ANOVA (Tables 7 and 8) as interactions and random effects are calculated differently in the MIXED model.

^a Relative slope position.

^b Surface convexity.

^c Direct insolation.

^d Barley yield 1994.

^e Maximum height.

^f Catchment slope.

^g Diffuse insolation.

(Table 8), of which 14% were attributed to GDD in April, May, July, and August (Table 7) in a separate analysis of covariance. Annual precipitation did not affect SOC (Table 8), however, monthly GSP in May, April, and September were important factors (Table 7). Input and diversity were also significant and accounted between 3 and 3.5% of variation in SOC (Tables 7 and 8). Profile curvature and catchment slope determined at the beginning of the study for the simulated plots were correlated with about 2% of variation in modelled SOC. The RED × DAG system resulted in the second highest SOC (Fig. 5) and second lowest MR (Fig. 6) among all other combinations of input and diversity.

3.3.2. Microbial respiration

Simulated MR by the EPIC model under climate change (2041–2070) driven by the RCM_GCM model ensemble (scenario 5) was highest in ORG (2.39 Mg C ha^{−1} y^{−1}) and RED (2.31 Mg C ha^{−1} y^{−1}) relative to HI input (2.14 Mg C ha^{−1} y^{−1}) which is attributed to higher tillage in ORG system, and accumulation of residue at the soil surface in RED. Differences between ORG and RED were not significant. In addition, microbial respiration for 2041–2070 (scenario 5) was highest in RED × DAP and second highest in ORG × DAG (Fig. 6) systems.

Simulations of MR by the EPIC model under observed historical baseline weather (1971–2000) (scenario 1) were significantly higher in ORG (2.05 Mg C ha^{−1} y^{−1}) and RED (1.97 Mg C ha^{−1} y^{−1}), and were lowest in HI (1.82 Mg C ha^{−1} y^{−1}). The amount of soil C lost as a result of MR was also highest in ORG × DAP (2.13 Mg C ha^{−1} y^{−1}) along with RED × DAP (2.37 Mg C ha^{−1} y^{−1}) and ORG × DAG (2.07 Mg C ha^{−1} y^{−1}). Under climate change predicted by the RCM_GCM model ensemble (scenario 5), simulated MR was lowest in RED × LOW and HI × LOW (Fig. 6), similar to that for MR simulated under observed historical baseline weather from 1971 to 2000 (scenario 1) (1.71 Mg C ha^{−1} y^{−1} in RED × LOW and 1.65 Mg C ha^{−1} y^{−1} in HI × LOW). Crop diversity accounted for more variability of MR under climate change (scenario 5) (lowest in LOW, highest in DAP) than input in ANOVA (Tables 7 and 8). Microbial respiration was second lowest in RED × DAG (Fig. 6). Combinations of RED with crop diversity resulted in the highest (RED × DAP) and lowest (RED × LOW) MR. These findings were reflected in partition analysis (Table 6). Microbial respiration under climate change was primarily correlated with June GDD and precipitation in May and July. Crop diversity was the second most important factor after June temperature (Table 7), followed by input,

August and June precipitation. Annual maximum and minimum MR, while annual precipitation was not found significant (Table 8). Terrain attributes such as relative slope position, and baseline variability of yield (barley yield in 1994) were also significant.

4. Discussion

Increased SOC has been related to soil health and quality (Poulton et al., 2018). For example, Powelson et al. (2012) and Thierfelder and Wall (2012) reported considerable improvements in soil physical properties related to zero tillage due to increases in SOC at 0–10 cm, despite minimal changes in SOC at greater depths. However Poulton et al. (2018), concluded that the key variable for soil C sequestration was the mass of SOC per unit area, also referred to as stock, not the concentration of C at the soil surface. In light of the conclusions by Poulton et al. (2018) the findings reported in this paper are of particular relevance because they: (1) discuss SOC and microbial respiration under changing climatic conditions and for alternative farm management for the 0–90 cm depth on mass basis and, (2) integrate long-term experimental data in combination with climate change and process-based modeling, which is one of the first analysis of this kind for the Canadian Prairies region.

In the past, scientists reported mixed results for the effects of field management practices, and referred to difficulties in detecting treatment effects, such as tillage and crop rotations, on SOC stocks. For example, Malhi et al. (2008) reported that the mass of measured SOC and light fraction organic C (LFOC) was greater due to no tillage, in comparison to conventional tillage. In similar research, return of crop residue to the soil, no-till, and balanced fertilization increased SOM and improved soil aggregation (Wu et al., 2006; Singh and Malhi, 2006; Malhi and Kutcher, 2007). However, Shrestha et al. (2013) reported a general decrease in SOC (0–15 cm) for comparisons of crop rotation, and minimum and no-till systems after 11 years, in contrast to increases (0–15 cm) reported by Congreves et al. (2015) for a 42 year study with low rates for frequently fallowed fields, and high rates for continuously cropped, well fertilized rotations (though the losses or gains in SOC might have been due to different initial SOC states in the two papers). Campbell et al. (2000) and Janzen et al. (1998) argued that changes in SOC between treatments may be detectable only after years or decades due to the heterogeneity and variability in soil texture, topography,

Table 7

Analysis of variance of the effects of input (main plots) and diversity (sub-plots) on soil organic C (Mg ha^{-1}) (0–90 cm) and microbial respiration (mass of soil C respired) ($\text{Mg ha}^{-1} \text{y}^{-1}$) with monthly growing season precipitation (GSP), growing degree days (GDD) and terrain attributes as covariates under future climate (2041–2070) scenario 5. The RCM_GCM models in ensemble are described in Table 3.

Source	df	Sum of squares	Significance	Percent of variation explained ^a
<i>Soil organic carbon</i>				
Input	2	675	*	2
Diversity[Input]	6	403	*	1
GSP April	1	90	*	< 1
GSP May	1	6224	*	16
GSP September	1	107	*	< 1
GDD April	1	223	*	1
GDD May	1	1228	*	3
GDD July	1	2527	*	7
GDD August	1	1230	*	3
Profile curvature	1	24	*	< 1
Catchment slope	1	4	*	< 1
Error	761	17,189		
C. total	778	38,464		
<i>Microbial respiration</i>				
Input	2	5	*	2
Diversity[Input]	6	15	*	5
GSP June	1	3	*	1
GSP August	1	6	*	2
GDD June	1	29	*	9
Relative slope posit.	1	1	*	< 1
Barley yield 1994	1	1	*	< 1
Error	765	239		
C. total	778	313		

NS – not significant.

* Significant at $P < 0.05$.

^a Percent variation for each term in the ANOVA calculated from C. total of sum of squares. Percent variation of independent variables in partition analysis (Table 6) may vary from ANOVA as interactions and random effects are calculated differently in the MIXED model.

fertility and other factors which affect soil C.

For the ACS study, Lemke (personal communication) reported that experimental long-term (1994–2013) topsoil SOC (0–15 cm) was highest in RED relative to other inputs, though not significant. In addition, Lemke et al. (unpublished data) reported that SOC at the 0–30 cm depth increased, by 6.0, 4.8, and 1.5 Mg ha^{-1} under RED, HI, and ORG system, respectively, from 1994 to 2012 soil C, though the difference was not significant. Malhi et al. (2009) also found no effect of input or crop diversity on SOC in the topsoil at the end of the second cycle of the ACS study in 2006. It is important to note that the studies by Lemke, and Malhi et al. (2009) focussed at SOC at 0–15 and 0–30 cm compared to 0–90 cm in the research we report. The relative magnitude of changes in SOC, due to tillage and cropping diversity from 1994 to 2013, was low for the ACS study relative to those reported by McConkey et al. (2003) for sub-humid regions in the Prairies. High sand content at this site also reduced the potential for accumulation of SOC, relative to clay soils which tend to accumulate soil C at higher rates (Liang et al., 2003). In addition, Shrestha et al. (2013) found no significant differences in SOC between minimum and no till systems in an 11-year field experiment in Swift Current, Saskatchewan based on simulations with the revised Century model. Differences in SOC between crop rotation and tillage systems may require several decades to become distinguishable in a semiarid climate with small and variable C inputs.

In our study, simulated effects of climate change, agricultural inputs, cropping diversity, and environmental factors were important predictors of variability in 0–90 cm SOC stocks and MR at the research site in Scott. Decreases in future SOC and increases in MR were

Table 8

Analysis of variance of the effects of input (main plots) and diversity (sub-plots) on soil organic C (Mg ha^{-1}) (0–90 cm) and microbial respiration (mass of soil C respired) ($\text{Mg ha}^{-1} \text{y}^{-1}$) with annual average maximum temperature (Tmax), annual average minimum temperature (Tmin), and cumulative annual average precipitation as covariates under future climate (2041–2070) scenario 5. The RCM_GCM models in ensemble are described in Table 3.

Source	df	Sum of squares	Significance	Percent of variation explained ^a
<i>Soil organic carbon</i>				
Input	2	960	*	2.5
Diversity[Input]	6	463	*	1
Tmax	1	12,278	*	32
Error	769	24,641		
C. total	778	38,464		
<i>Microbial respiration</i>				
Input	2	957	*	2.5
Diversity[Input]	6	463	*	1
Tmin	1	16,336	*	42
Error	769	20,583		
C. total	778	38,464		
<i>Microbial respiration</i>				
Input	2	983	*	2.5
Diversity[Input]	6	462	*	1
Precipitation	1	1019	NS	–
Error	769	35,900		
C. total	778	38,464		
<i>Microbial respiration</i>				
Input	2	9	*	3
Diversity[Input]	6	33	*	10.5
Tmax	1	26	*	8
Error	769	245		
C. total	778	313		
<i>Microbial respiration</i>				
Input	2	9	*	3
Diversity[Input]	6	33	*	10.5
Tmin	1	37	*	12
Error	769	233		
C. total	778	313		
<i>Microbial respiration</i>				
Input	2	9	*	3
Diversity[Input]	6	33	*	10.5
Precipitation	1	1	NS	–
Error	769	269		
C. total	778	313		

NS – not significant.

* Significant at $P < 0.05$.

^a Percent variation for each term in the ANOVA calculated from C. total of sum of squares. Percent variation of independent variables in partition analysis (Table 6) may vary from ANOVA as interactions and random effects are calculated differently in the MIXED model.

attributed to an increase in minimum temperature of up to 2 °C on an annual basis, extended growing seasons, and an increase in average precipitation of 11%. The increase in MR was due to higher soil temperatures throughout the year, and during the growing season, resulting in higher losses of C from the SOC stock relative to historic climate scenarios. Variation in historical and future scenarios for these variables was driven by fluctuations in temperature and precipitation simulated in the driving GCM, which was set as a boundary condition for each individual RCM_GCM pair. The decline in SOC was also attributed to the initial high SOC in 1994, and 90 year period since the native prairie was first cultivated. Crowther et al. (2016), also found that the increase in future temperature was an important factor in SOC loss and the effects of warming are contingent on the size of the initial SOC stock, with considerable losses occurring in high-latitude areas. Poulton et al. (2018) also reported low SOC concentrations of 30.1 Mg ha^{-1} (1.15%) and 28.8 Mg ha^{-1} (1.0%) (0–23 cm) at two research sites in the United Kingdom which were in arable cropping for several hundred years, reflecting a steady decline of SOC over time due to cultivation.

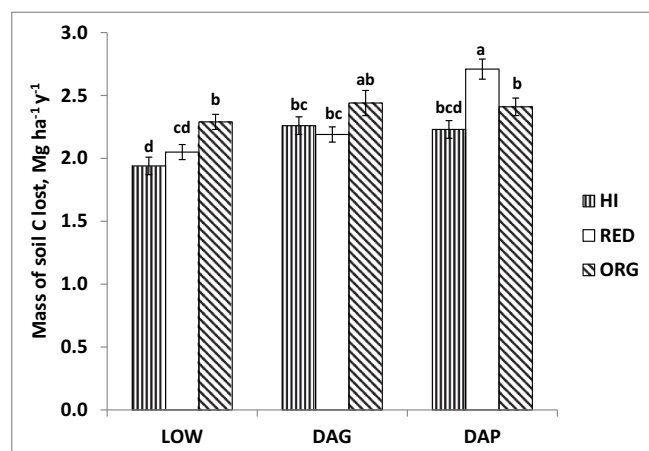


Fig. 6. Effects of input (high – HI; reduced – RED; organic – ORG) and cropping diversity (low – LOW; diversified annual grains – DAG; diversified annuals and perennials – DAP) on 30-year (2041–2070) average mass of soil C lost through microbial respiration calculated from annual values for 2041–2070 simulated by the EPIC model under future climate (scenario 5). Models in ensemble are listed in Table 3. Means within and between each combination followed by the same letter do not differ at $P = 0.05$, based on Tukey's HSD. Error bars represent ± 1 standard error of the mean calculated from annual values for 2041–2070 simulated with EPIC model. $n = 779$.

The importance of GSP, as one of the driving factors which affected future SOC, was also described by Congreves et al. (2015), who reported that, among other factors, GSP was an important factor which affected residue C input in a 42-year crop rotation experiment conducted at Swift Current, Saskatchewan. Our findings on GSP were similar to those of Shrestha et al. (2013) and Huxman et al. (2004), who concluded that the interplay between precipitation and C balance is complex in semiarid climate and based on amount and timing, increased precipitation may enhance SOC decomposition more than C gains from C inputs which may result in a net loss of SOC. Fan et al. (2019) also noted that SOC (0–20 cm) may be lost in interior western Canada due to high initial SOC and high precipitation. However, Fan et al. (2019) concluded that SOC stocks would increase on a national scale due to increased crop yield and root inputs in the future.

Tillage and cropping diversity also influenced the relative rates of decline of SOC content over time, when past and future climate scenarios were assessed with field and crop management practices of the ACS study. We attributed the difference in future SOC for combinations of inputs and diversity to: (1) tillage frequency; (2) increased plant biomass under DAP, and (3) lower inputs of biomass and C to the soil under DAG relative to DAP, which resulted in a gradual loss of SOC in ORG \times DAG. The significant effect of tillage on SOC reported in this study was similar to that reported by Malhi et al. (2008), who concluded that the mass of SOC and light fraction organic C (LFOC) was greater due to no tillage, in comparison to conventional tillage. Similarly, Jarecki et al. (2018) reported that more diversified rotations had the largest increases in SOC simulated by the DNDC model under climate change for a research site in Woodslee, Ontario. Sainju et al. (2015) also described a lower rate of decrease in SOC in treatments with less tillage over a 30 year period in Montana. Furthermore, Chatskikh et al. (2008) concluded that reduced tillage in dry climates

may be an effective measure for enhancing C sequestration due to effects on microbial respiration, changes in SOM turnover and soil water retention. Finally, Arcand et al. (2017) reported approximately 36% more dissolved organic C in RED, compared to ORG management, regardless of cropping history. In our study, simulated differences were related to tillage frequency with highest SOC in RED input (zero tillage), and lowest under HI (conventional tillage).

We attributed the higher rates in future MR under RED \times DAP and ORG \times DAG systems due to greater root biomass of perennial plants in DAP, such as alfalfa, which contributed more C to the soil compared to other systems. In addition, crop residue increased at the soil surface in RED compared to other input levels. This resulted in greater MR in RED \times DAP compared to other systems. Arcand et al. (2016), also reported approximately 27% higher respiration rates in RED compared to ORG management in an incubation experiment conducted on soils collected from the ACS site. Amiro et al. (2017), found that rotations with annual crops lost a net of $78 \pm 51 \text{ g C m}^{-2} \text{ y}^{-1}$ due to respiration over an 11-year period at Glenlea Manitoba. During the four-year period of the perennial phase of this study, the annual-perennial cropping system lost a net of $66 \text{ g C m}^{-2} \text{ y}^{-1}$ compared to a loss of $187 \text{ g C m}^{-2} \text{ y}^{-1}$ for the annual cropping system. Precipitation, temperature, and cropping diversity significantly influenced MR fluxes in our study, similar to research by Glenn et al. (2010). Carbon dioxide fluxes in their study were a source of $3170 \text{ kg C ha}^{-1}$ after harvest in a three year maize-faba-spring wheat rotation with reduced and more intensive tillage treatments at a research site in Glenlea Manitoba.

In our study, the RED system had several environmental and agronomic advantages, relative to other combinations of input and diversity. The mass of SOC was second highest in the RED \times DAG system, and MR flux was second lowest, among all other combinations of input and diversity. Long-term wheat yield (2041–2070) simulated by the EPIC model was highest in the RED relative to the other input systems (Lychuk et al., 2017a). Furthermore, simulated nitrate-N leachate losses were lowest in RED \times DAG among all other combinations of input and diversity (unpublished data). In summary, the RED \times DAG system increased yield and reduced losses of SOC, respired C, and nitrate in simulations of historical and climate change scenarios.

5. Conclusions

Climate change and management affected simulations of soil processes and properties in this case study. The consequences of climate change for carbon stocks were relatively low, with a slow decrease in mass over time due to a gradual increase in respiration. The impact of tillage management and crop diversity on SOC stocks and MR was low, relative to the seasonal distribution of precipitation and temperature, and annual temperature governed by climate change. However the application of reduced tillage combined with diverse annual grain crops, reduced the impact of climate change on soil properties and the environment. Thus, RED \times DAG represented a sustainable, adaptive management tool in this case study, in the context of seasonal and annual variations in temperature and precipitation due to climate change. Reduced tillage and input management influenced crop yield and mitigated the effects of climate change and seasonal variability of temperature and precipitation in simulations. Thus, reduced input systems may provide an adaptive strategy to growers and policy analysts for climate change in the Canadian Prairies. However, further research is required to confirm these relationships, for other sites and case studies.

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Appendix A

Table A1

Regional distribution of growing season (April 15 – September 15) air temperatures and precipitation under observed historical baseline (HIST. BASELINE, 1971–2000) weather and deviations from the baseline predicted by the four Regional Climate Models^a (RCMs) and their Global Climate Models (GCMs) as boundary conditions over the future (2041–2070) simulation period.

GCM driven RCM simulation	Maximum daily air temperature (°C)	Minimum daily air temperature (°C)	Precipitation (mm)
1971–2000, HIST. BASELINE	20.36	6.90	243.23
CRCM_CGCM3	0.07	– 0.64	83.16
CRCM_CCSM	4.85	0.58	– 36.69
RCM3_GFDL	– 4.20	1.43	206.33
RCM3_CGCM3	– 2.47	2.37	192.50
WRFG_CGCM3	1.04	2.29	– 47.90
WRFG_CCSM	1.90	2.46	– 94.60
HRM3_GFDL	2.72	4.77	61.52

^a Refer to Table 3 and text for the description of RCM_GCM models.

Table A2

Historical observed baseline (Scott 1971–2000) and future (2041–2070) monthly growing season precipitation (GSP) and growing degree days (GDD). Future GSP and GDD were predicted by the RCM_GCM models and ensemble model average. Models are listed in Table 3.

Model	Growing season precipitation, mm month ^{–1}						Growing degree days					
	April	May	June	July	Aug.	Sept.	April	May	June	July	Aug.	Sept.
Scott 1971–2000	15.48a	38.43a	59.60a	69.04a	44.96a	16.28a	18.58a	177.42a	303.33a	372.34a	345.55a	106.45a
CRCM_CGCM3	16.47ab	68.18d	83.35c	85.25d	58.24d	13.75c	0.00g	140.32f	316.83b	415.64d	327.20d	83.75d
CRCM_CCSM	18.62bc	46.84b	48.21e	44.69g	28.97f	11.16d	11.63f	243.89e	452.11e	529.34f	429.98c	99.14b
RCM3_GFDL	23.22d	77.37e	117.55d	130.10b	70.85c	27.37b	0.00g	96.44g	309.53ab	387.14b	266.47g	63.61e
RCM3_CGCM3	25.52e	82.40f	119.51d	123.97c	75.29b	16.39a	12.21f	149.04f	302.82a	400.31c	325.95d	117.23f
HRM3_GFDL	34.10f	83.09f	71.83b	68.95a	39.05e	13.76c	137.05c	393.76b	514.25f	497.51g	283.58f	60.49e
WRFG_CGCM3	13.27g	44.70b	42.72f	56.76f	32.14f	6.22e	103.62d	304.37c	377.43c	396.04c	298.69e	102.34ab
WRFG_CCSM	9.30h	37.09a	38.74f	31.22h	21.31g	11.06d	77.95e	278.21d	388.51d	445.54e	376.17b	91.48c
Ensemble average	20.07c	62.81c	74.56b	77.28e	46.55a	14.24c	44.34b	183.28a	380.21cd	438.79e	329.72d	88.26cd
Standard error of the difference ^a	0.71	1.61	1.72	1.87	1.32	0.64	1.73	3.31	2.68	2.75	2.82	1.99

Letters within the same column indicate Tukey HSD mean differences at $P < 0.05$.

^a Tukey HSD test standard error of the difference.

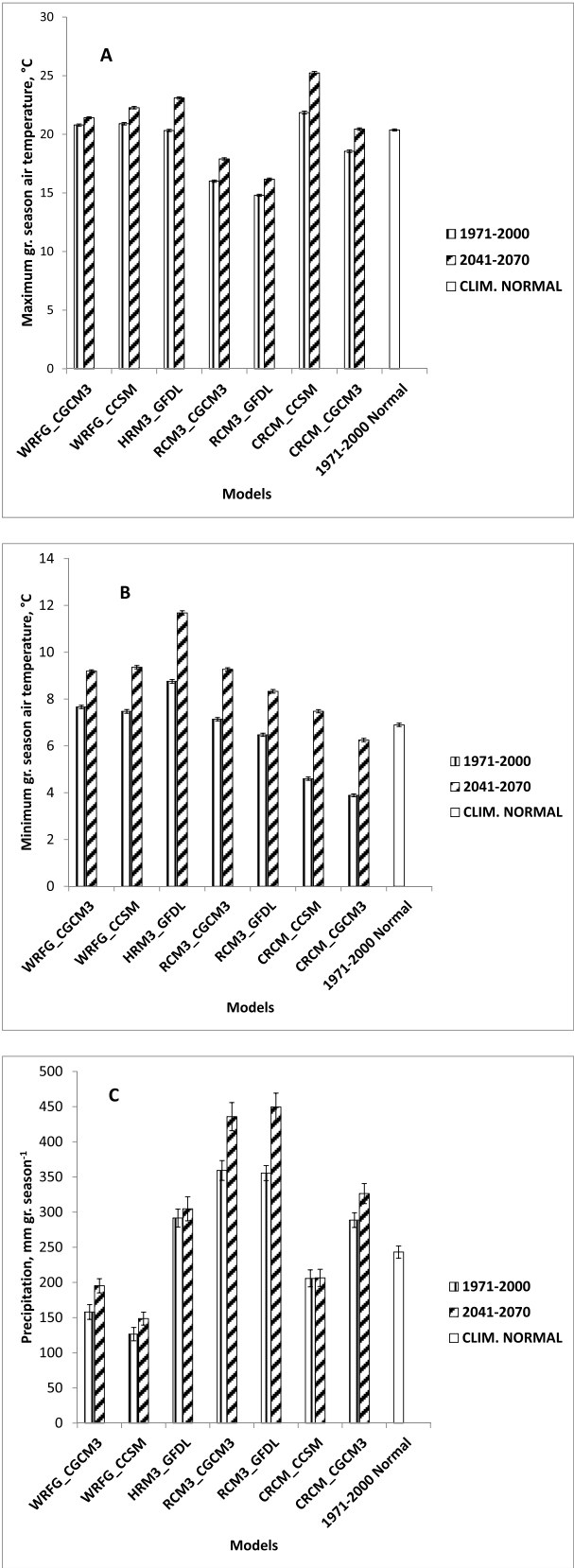


Fig. A1. Growing season average maximum (A), minimum (B) temperatures (°C) and precipitation (C) (mm) over RCM_GCM driven historic (1971–2000, rectangles with vertical lines) and future (2041–2070, striped rectangles) weather predicted by each of the seven RCM_GCM models. The observed historical baseline weather 1971–2000 climate normal value for temperature and precipitation is shown by non-colored rectangle. Models are listed in Table 3. Error bars represent standard error of the mean. $n = 7011$.

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